Latvian and Lithuanian Named Entity Recognition with TildeNER

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Abstract

In this paper the author presents TildeNER – an open source freely available named entity recognition toolkit and the first multi-class named entity recognition system for Latvian and Lithuanian languages. The system is built upon a supervised conditional random field classifier and features heuristic and statistical refinement methods that improve supervised classification, thus boosting the overall system's performance. The toolkit provides means for named entity recognition model bootstrapping, plaintext document and also pre-processed (morpho-syntactically tagged) tab-separated document named entity tagging and evaluation on test data. The paper presents the design of the system, describes the most important data formats and briefly discusses extension possibilities to different languages. It also gives evaluation on human annotated gold standard test corpora for Latvian and Lithuanian languages as well as comparative performance analysis to a state-of-the art English named entity recognition system using parallel and strongly comparable corpora. The author gives analysis of the Latvian and Lithuanian named entity tagged corpora annotation process and the created named entity annotated corpora.

Keywords: named entity recognition, Latvian and Lithuanian languages, bootstrapping

1. Introduction

Named entity recognition (NER) has been actively researched for over 20 years. Most of the research has, however, been focussed on resource rich languages, for instance, English French and Spanish. The scope of this paper covers the task of named entity recognition for two under-resourced languages – Latvian and Lithuanian. The author presents an open source freely available toolkit named *TildeNER* that makes use of existing supervised learning methodology (for instance, the Stanford NER conditional random field classifier (Finkel et al., 2005)) enriched with heuristic refinement methods in order to bootstrap NER models using unlabelled data, thus, creating a "*highly supervised*" semi-supervised named entity recognizer.

Latvian and Lithuanian are the state languages of two European Union member countries - Latvia and Lithuania. Both languages feature rich morphology with high morphological ambiguity and a relatively free order of constituents in sentences, thus, making the task of named entity recognition more difficult than, for instance, for English.

The current dominant approach to developing named entity recognition systems is supervised learning (Nadeau and Sekine, 2007). This, however, means that a prerequisite for NER model training is a large named entity (NE) annotated data corpus. For resource rich languages this is not an issue, but for under-resourced languages (for instance, the Baltic languages) is. For Latvian and Lithuanian there has been very little previous research in the field of named entity recognition. Most of the existing research has dealt with only toponym recognition, for instance, Skadiņa (2009) describes toponym recognition from image annotations using lexicons and patterns. Also the lack of annotated named entity corpora for both languages does not allow (without significant financial input for corpora creation) the development of a truly supervised NER system. Because of the available resource constraints, for Latvian and Lithuanian a semi-supervised NER system development approach was selected, more precisely, bootstrapping. The systems presented in the paper are, therefore, the first multi-class NER tools created for Latvian and Lithuanian. The main reason for the development of the Latvian and Lithuanian NER systems has been to tag NEs in comparable corpora for further bilingual NE alignment using NE mapping methods in the ACCURAT project[1]. It is also planned to use the NER systems as a pre-processing step in machine translation in order to create NE-aware translations.

The next chapter gives a description of the NE-annotated corpora followed by a section on the design and methods applied in *TildeNER* and evaluation in section four. The paper is finalized with conclusions and a discussion of future work.

2. Annotated Corpora

For the task of named entity recognition relatively small NE annotated corpora was created. The corpora for both languages consists of IT localization (software reviews, manuals and other IT related articles), news (current news from news web portals) and Wikipedia articles in equal proportions. The first two parts were acquired using comparable corpora web crawling tools developed within the ACCURAT project[2]. The corpora statistics is shown in Table 1.

For the annotation task, NE mark-up guidelines[3] were prepared. The guidelines are mostly compliant with the MUC-7 (Chinchor, 1998) NE annotation guidelines (adaptation to Latvian and Lithuanian was performed as

[1] Report on information extraction from comparable corpora,
[2] Tools for building comparable corpus from the Web, public deliverable of the project ACCURAT, 2011.
[3] Published as part of TildeNER in the „Toolkit for multi-level alignment and information extraction from comparable corpora", public deliverable of the project ACCURAT, 2011.

well as minor contradictions were resolved). The following NE categories were annotated: organization, person name, location, product, date, time, money.

	Latvian	Lithuanian
Document count		
Seed	40	37
Development	25	33
Test	66	55
Total	**131**	**125**
Word count		
Seed	20 959	18 852
Development	10 053	17 827
Test	41 208	36 239
Total	**72 220**	**72 918**

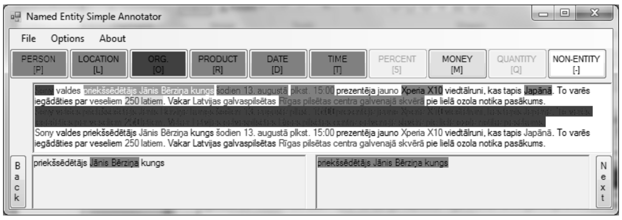
Table 1: Latvian and Lithuanian corpora statistics.

The corpora were annotated by two annotators and disagreements were resolved by a third annotator for both languages. The inter-annotator agreement between the first two annotators using the Cohen's Kappa statistic (Cohen, 1968) is 0.885 for Latvian and 0.822 for Lithuanian. This score, however, represents the overall complexity of the corpora including non-entities strictly classified as non-entities by both annotators. This score does not represent the actual NE annotation complexity and difficulties in NE border detection; that is, adding or removing non-entity data (tokens/sentences) will result in respectively higher or lower inter-annotator agreement. Therefore, separate NE category and NE border detection inter-annotator agreement scores are given in Table 2. The token level agreement scores do not consider cases where both annotators annotated a token as a non-entity.

	Latvian	Lithuanian
Full NE agreement		
NE border agreement	0.749	0.671
Category agreement on matching borders	0.964	0.967
Token level agreement		
LOCATION	0.790	0.703
ORGANIZATION	0.708	0.623
PERSON	0.932	0.910
PRODUCT	0.641	0.683
DATE	0.812	0.696
TIME	0.713	0.662
MONEY	0.785	0.599
Total token agreement	**0.807**	**0.723**

Table 2: Inter-annotator agreement on Latvian and Lithuanian corpora.

In the process of annotation a tool named *NESimpleAnnotator* was used (released together with *TildeNER*). The annotation tool allows fast one-dimensional (non-hierarchical) annotation of NEs of the defined categories. The annotation tool also features disambiguation functionality for a judge. The annotation tool in the disambiguation view is shown in Figure 1.



Sony valdes priekšsēdētājs Jānis Bērziņa kungs šodien 13. augustā plkst. 15:00 prezentēja jauno Xperia X10 viedtālruni, kas tapis Japānā. To varēs iegādāties par veseliem 250 latiem. Vakar Latvijas galvaspilsētas Rīgas pilsētas centra galvenajā skvērā pie lielā ozola notika pasākums.

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priekšsēdētājs Jānis Bērziņa kungs

priekšsēdētājs Jānis Bērziņa kungs

Figure 1: Disambiguation view of *NESimpleAnnotator*

After annotation both corpora were split in seed, development and test sets. The development set is used in refinement method parameter tuning and feature function selection processes and the test set is used for final evaluation. The NE statistics in the disambiguated corpora is shown in Table 3 for both Latvian and Lithuanian.

NE Type	Seed	Development	Test
Latvian			
DATE	498	249	843
LOCATION	682	479	1 453
MONEY	123	18	148
ORGANIZATION	464	219	966
PERSON	267	172	601
PRODUCT	381	103	382
TIME	200	46	107
Total	**2 615**	**1 286**	**4 500**
Lithuanian			
DATE	548	297	711
LOCATION	470	563	1 086
MONEY	150	147	313
ORGANIZATION	240	275	603
PERSON	202	169	604
PRODUCT	174	310	389
TIME	67	57	109
Total	**1 851**	**1 818**	**3 815**

Table 3: Latvian and Lithuanian NE annotated corpora statistics.

The NE annotated data is stored in plaintext format containing MUC-7 style NE tags. A format sample is given in Figure 2. This format is also used when *TildeNER* performs automatic NER on user provided plaintext documents.

```
<ENAMEX TYPE="PERSON">Bruno Kalniņš</ENAMEX>
dzimis <TIMEX TYPE="DATE">1899. gada 7.
maijā</TIMEX> <ENAMEX
TYPE="LOCATION">Tukumā</ENAMEX> ievērojamo
sociāldemokrātu <ENAMEX TYPE="PERSON">Paula
Kalniņa</ENAMEX> un <ENAMEX TYPE="PERSON">Klāras
Kalniņas</ENAMEX> ģimenē.
```

Figure 2: Sample of Latvian human annotated NE corpora using *NESimpleAnnotator*

3. System Design

TildeNER is a named entity recognition toolkit that consists of multiple workflows for NER model training, NE tagging and evaluation[4]. In training and tagging as a machine learning (ML) component *TildeNER* uses the conditional random field classifier *StanfordNER* (Finkel et al., 2005), which contains a large set of feature functions required in a supervised NER system (and does not require inventing a wheel a second time). The *TildeNER* system is developed in Perl and the *StanfordNER* system is a *Java* application. Both systems run on *Winodws* and *Linux* operating systems.

3.1 Feature Function Selection

The feature functions for both Latvian and Lithuanian were selected using iterative minimum error-rate training. The method starts with a seed feature function set and in each iteration trains multiple (depending on the number of altering feature functions) NER models with altered (set to "*true*" or "*false*" or assigned a different value) feature functions where each model has a different feature function altered. The feature function set of the model, which increases the F-measure the most is selected as the base set for the next iteration.

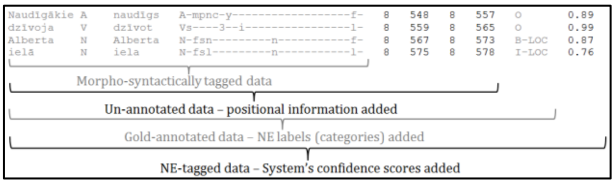
Although such an iterative approach allows finding only the local maxima it is sufficient to select good performance feature functions. In the authors experiments in every iteration 85 different models were trained and the performance on Latvian development data increased from a token level F-measure of 63.29 to 69.47, which gives a significant increase on the system's performance (although, on development data).

3.2 Data Pre-processing

The human annotated data and unlabelled data that is used in NER model training or tagging is pre-processed using a maximum entropy based morpho-syntactic tagger (Pinnis and Goba, 2011), which tokenizes, lemmatizes and morpho-syntactically tags the data. The tag is positional and contains 28 categories (for instance, part of speech, verb tense and mode, gender, number, case, required number and case agreement, etc.). The output of the tagger is tab-separated as shown in Figure 3.

After morpho-syntactic tagging, positional information is added in order to trace every token from the tab-separated document back to its positions in the plaintext input document. In the case of gold annotated data also NE categories are assigned to each token. As introduced in the CoNLL 2002 conference (Tjong Kim Sang, 2002) the author also uses the BIO scheme for annotation of non-entity tokens and NE tokens (for instance, "B-ORG" and "I-ORG" for first and further tokens of an organization).

The data pre-processing step introduces a new feature function – the value of the morpho-syntactic tag. This feature function has been integrated in the *StanfordNER* conditional random field (CRF) classifier used by *TildeNER*. It can be used as additional feature to describe the context around a token in the range from one to N (depending on the configuration) tokens to the left and to the right from each token. The whole positional tag is used as a feature.



```
Naudīgākie A    naudīgs   A-mpnc-y-----------------f-   8   548   8   557   O       0.89
dzīvoja    V    dzīvot    Vs----3--i---------------l-   8   559   8   565   O       0.99
Alberta    N    Alberta   N-fsn---------n----------f-   8   567   8   573   B-LOC   0.87
ielā       N    iela      N-fsl---------n----------l-   8   575   8   578   I-LOC   0.76
```

Morpho-syntactically tagged data
Un-annotated data – positional information added
Gold-annotated data – NE labels (categories) added
NE-tagged data – System's confidence scores added

Figure 3: Pre-processed data format sample of different intermediate output files within *TildeNER* workflows

A new language in *TildeNER* can be integrated by providing a morpho-syntactic tagger that tokenizes and tags data in a tab-separated format as defined in Figure 3. The morpho-syntactic tag, however, is optional and for morphologically simpler languages it can also be omitted by changing NER model training and NE tagging property files required by the Stanford NER CRF classifier.

3.3 NER Model Bootstrapping

The NE annotated corpora for Latvian and Lithuanian are relatively small compared to data sets that are used, for instance, for English NER system development and model training. Therefore, *TildeNER* features a NER model bootstrapping module, which employs a bootstrapping method similar to Liao and Veeramachaneni (2009).

In order to bootstrap a NER model the system requires a set of seed, development and test data (human annotated data). Additionally to the human annotated data unlabelled data is required (for instance, in author's experiments articles from Wikipedia and Web news were used as sources of unlabelled data). All four sets have to be pre-processed in order to run the bootstrapping workflow. The overall bootstrapping design, including pre-processing steps, is shown in Figure 4. Once all data is available, the bootstrapping system iteratively:

- Trains a NER model. In the first iteration only seed data is used as training data. In further iterations, additionally to the seed data, new training data, which

[4] A detailed list of available workflows is listed in the technical documentation of *TildeNER*.

is extracted in previous iterations, is used.

- Evaluates the trained model on development and test data. The system provides also functionality that enforces only positive iteration usage (specified in the configuration), dropping all iterations that decrease performance on the development set. Iteration is considered positive if it increases either precision, recall or F-measure (also defined through the configuration).

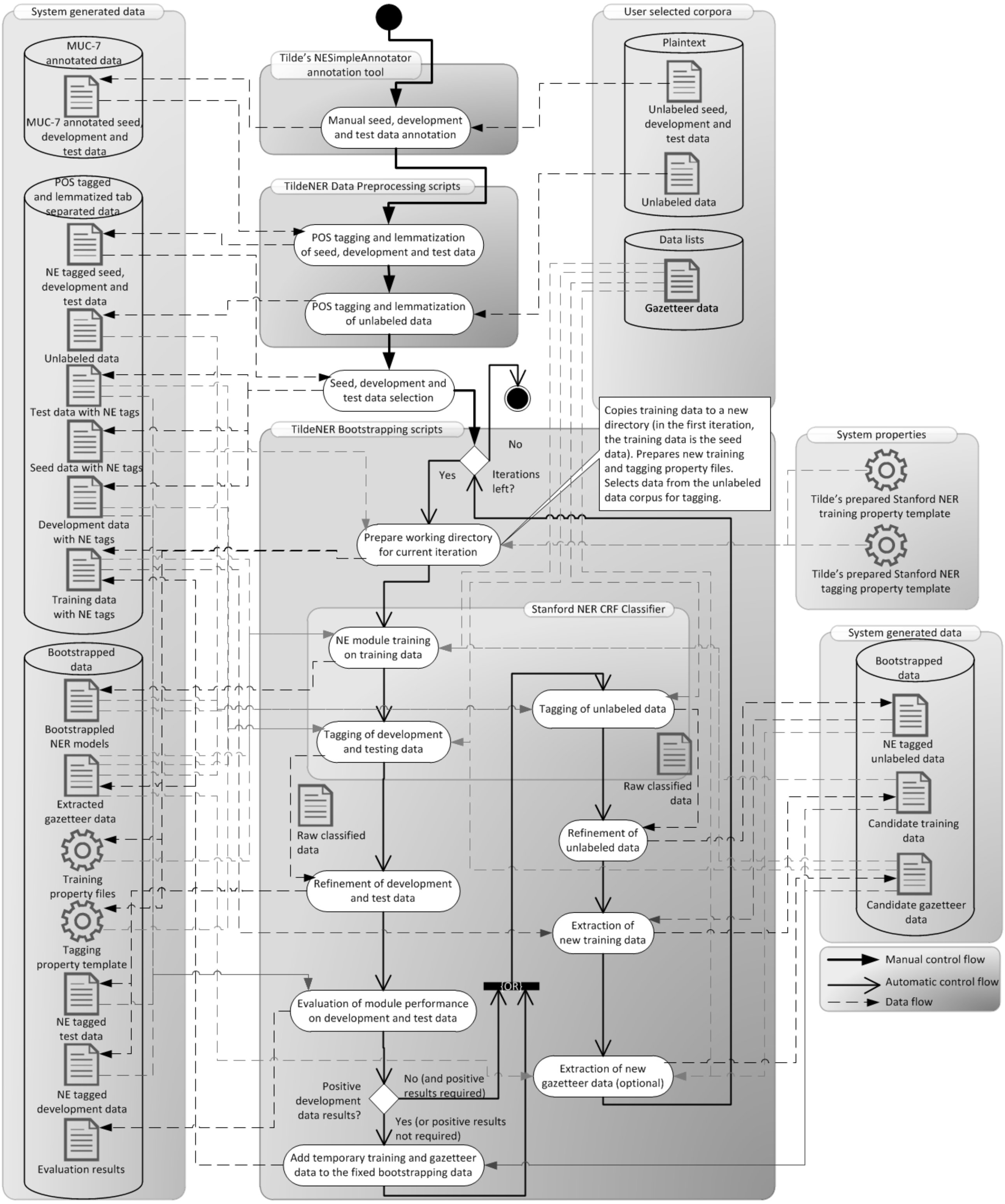

System generated data
MUC-7 annotated data
MUC-7 annotated seed, development and test data
POS tagged and lemmatized tab separated data
NE tagged seed, development and test data
Unlabeled data
Test data with NE tags
Seed data with NE tags
Development data with NE tags
Training data with NE tags
Bootstrapped data
Bootstrappled NER models
Extracted gazetteer data
Training property files
Tagging property template
NE tagged test data
NE tagged development data
Evaluation results
Tilde's NESimpleAnnotator annotation tool
Manual seed, development and test data annotation
TildeNER Data Preprocessing scripts
POS tagging and lemmatization of seed, development and test data
POS tagging and lemmatization of unlabeled data
Seed, development and test data selection
TildeNER Bootstrapping scripts
No
Yes
Iterations left?
Copies training data to a new directory (in the first iteration, the training data is the seed data). Prepares new training and tagging property files. Selects data from the unlabeled data corpus for tagging.
Prepare working directory for current iteration
Stanford NER CRF Classifier
NE module training on training data
Tagging of unlabeled data
Tagging of development and testing data
Raw classified data
Raw classified data
Refinement of unlabeled data
Refinement of development and test data
Extraction of new training data
OR
Evaluation of module performance on development and test data
Positive development data results?
No (and positive results required)
Yes (or positive results not required)
Extraction of new gazetteer data (optional)
Add temporary training and gazetteer data to the fixed bootstrapping data
User selected corpora
Plaintext
Unlabeled seed, development and test data
Unlabeled data
Data lists
Gazetteer data
System properties
Tilde's prepared Stanford NER training property template
Tilde's prepared Stanford NER tagging property template
System generated data
Bootstrapped data
NE tagged unlabeled data
Candidate training data
Candidate gazetteer data
Manual control flow
Automatic control flow
Data flow

Figure 4: Design of the bootstrapping workflow

- Tags the unlabelled data with the newly trained NER model. In the case if the configuration requires only positive iteration data propagation and the current trained model decreases performance, unlabelled data is tagged with a model from the last positive iteration.
- Extracts new training data. After the unlabelled data is tagged with the trained NER model, new training data is extracted. Sentences that contain NEs, which have been annotated with the heuristic and statistical refinement methods, are ranked and the top *N* sentences of each NE category are selected as new training data. It is important in this step to use good refinement methods that are able to tag new and unseen by the supervised classifier NEs. If the raw data that the NER classifier outputs is used, the bootstrapping learns only the cases that it already knows as the supervised classifier's performance on unseen data is unreliable.
- Extracts new gazetteer data from the newly tagged unlabelled data. This step is optional, but can be used in automatic gazetteer bootstrapping. The system also allows using the extracted NE lists in training of further iteration NER models.

3.4 Refinement Methods

In NER model bootstrapping as well as tagging, *TildeNER* applies refinement methods in order to improve upon the NE classification results produced by the *StanfordNER* CRF classifier. During bootstrapping the refinements help finding new unseen data examples and in tagging refinements allow achieving either better precision or recall (depending on the configuration of the refinement methods).

Refinement methods are functions that analyse a document and re-classify tokens or sequences of tokens as named entities or non-entities. The following refinements have been implemented so far in *TildeNER*:

- Removal of unlikely NEs. Named entities that are classified by the CRF classifier below a configured threshold are re-classified as non-entities (increases precision).
- Consolidation of equal lemma sequences. In NER a common assumption is to classify equal NEs with the same category (one sense per discourse rule). This method analyses such cases and decides whether for certain NEs, which are classified as being of multiple categories, one category, which is the most likely, can be identified. Misclassified entities in such situations are re-classified (increases precision). This method is important as the CRF classifier does not observe the whole context, but rather a limited window and is not able to realise the one sense per discourse rule.
- Enforcing equal lemma sequences to be tagged (increases recall). Similarly as in the previous method, the CRF classifier tends not only misclassify, but also miss some NEs in different contexts (mostly in contexts unknown to the NER model). This method classifies lemma sequences that are misclassified as non-entities if there exists a NE that is classified with a confidence score of over a configurable threshold and has the same lemma sequence as the non-entity sequence. This refinement method also enforces the one sense per discourse rule.
- NE border correction for entities, which contain an odd number of quotation marks or brackets (increases both precision and recall). When bootstrapping, the new training data tends to contain classified sequences that lack, for instance, a bracket or a quotation mark, because the classifier's confidence has been too low to tag the misclassified token as part of the NE. This issue occurs mostly for NEs spanning over five and more tokens. If not controlled, such cases decrease system's performance over bootstrapping iterations. Therefore, this method tries to expand or reduce the NEs containing bracketing and quotation mistakes.
- Artefact removal methods (increase precision). Applying the NER system to different domains, some in-domain artefacts (for instance, hyperlinks in web crawled documents, some leftover mark-up from corpora processing, etc.) can occur in texts.
- Person name analysis (increases recall). As person names may consist of multiple tokens (first name, middle name, last name, title, etc.), the refinement method splits all person NEs, which CRF classifier's confidence score is above a configurable threshold, in separate tokens and tags non-entity tokens that match with the NEs respective tokens.
- Sentence beginning classification validation (increases recall). Sentence beginnings have proven to be difficult cases for NER as the capitalized tokens may be misleading. If the CRF classifier classifies a token as a NE, but it can be found elsewhere in the same document as a common (lowercased) word and lowercased, the sentence beginning misclassified NE is re-classified as a non-entity.

Refinement methods can be applied in any required sequence by passing a "*refinement order definition string*" when running *TildeNER*. This allows boosting the system's performance by either recall or precision (and in some cases by both).

4. Evaluation

4.1 Non-comparative Evaluation

As a baseline the author uses the supervised system (without bootstrapping and refinements) trained with only the *StanfordNER* CRF classifier using the feature functions selected in the iterative minimum error rate training. Table 4 shows the baseline performance with an F-measure of 54.28 for Latvian and 62.70 for Lithuanian on full NEs (border detection and equal categories).

An obvious question is: "*Why is there such a huge difference*?" The answer is quite simple – the test sets and training sets wary in content complexity. For instance, the Latvian texts feature automatically web crawled data, which includes also extracted tables with vague structure (space or tab separated), many short fragments with missing context, as well as many fragments with comma separated NEs.

System	Latvian				Lithuanian			
	Precision	Recall	Accuracy	F-measure	Precision	Recall	Accuracy	F-measure
Baseline (Only CRF Classifier)								
Token	74.70	56.23	91.02	64.16	74.44	63.54	92.30	68.56
Full NE	62.43	48.01	-	54.28	67.42	58.60	-	62.70
Baseline (CRF + refinement methods) tuned for precision								
Token	86.47	41.51	88.86	56.09	**84.04**	53.74	91.53	65.56
Full NE	75.61	35.05	-	47.90	**77.01**	49.63	-	60.36
Baseline (CRF + refinement methods) tuned for F-measure								
Token	74.63	57.15	91.17	64.73	76.31	63.50	**92.47**	69.32
Full NE	62.32	49.66	-	55.27	68.57	59.39	-	63.65
Bootstrapped (CRF + refinement methods + bootstrapping) for better precision								
Token	**87.27**	45.17	89.57	59.53	-	-	-	-
Full NE	**79.18**	41.85	-	54.76	-	-	-	-
Bootstrapped (CRF + refinement methods + bootstrapping) for better F-measure								
Token	75.55	**61.34**	**91.86**	**67.71**	76.90	**63.77**	92.42	**69.72**
Full NE	64.98	**56.06**	-	**60.19**	71.32	**59.91**	-	**65.12**

Table 4: Evaluation results on test data.

The Lithuanian corpora, on the other hand, is manually selected and extracted from news portals, Wikipedia and other sources, therefore, features less complex structures. All these points result in lower Latvian results on the test set and if comparison between the two system evaluations is done, test data complexity has to be taken into account.

Once the baseline systems were prepared, the refinement method parameters and the refinement method application sequence were tuned on the development set data. As a result two refinement order definition configurations have been created:

- A configuration, which allows increasing precision by up to 10% and more (at the cost of recall) with the following refinement order definition string: "*L N S F T_0.8 C P_0.8 R_0.8*". The string states: after CRF classification the following refinements are applied to the raw classified data in the exact sequence:
  - NE border correction for entities with odd number of quotation marks or brackets ("*L*").
  - Artefact removal methods ("*N*" and "*S*").
  - Sentence beginning classification validation ("*F*").
  - Tagging of equal lemma sequences with a confidence score threshold of 0.8 ("*T_0.8*").
  - Consolidation of equal lemma sequences ("*C*").
  - Person name analysis with a confidence threshold of 0.8 ("*P_0.8*").
  - Removal of unlikely NEs with a confidence threshold of 0.8 ("*R_0.8*").
- A configuration, which allows increasing F-measure (although, only up to 1%) with the following refinement order definition string: "*L N S F C T_0.6 P_0.5*".

The evaluation results using refinement methods on top of the baseline CRF based system are given in Table 4.

Using bootstrapped models (with the respective refinement configurations), precision and F-measure can be increased by up to 4.92% over the refined supervised results for full NEs and up to 16.55% for precision and up to 5.91% for F-measure over the baseline systems. For comparison, Czech (Kravalová and Žabokrtský, 2009), who also feature a morphologically rich language with different NE capitalization rules as in English, achieve an F-measure of 0.71 using 10 NE categories and a corpus twice as large).

In the precision bootstrapped NER model for Latvian a total of 75% of errors are caused by missing NE's in the tagged data, 15% are caused by incorrect border detection and the remaining 10% are wrong category classification mistakes.

4.2 Experimental Comparative Evaluation

In order to better understand the performance figures and to be able to better compare results to different language NER systems, for experimental purposes a comparative evaluation on parallel and strongly comparable corpora was performed. The reasoning, why parallel and strongly comparable corpora is used, is such that in parallel (and also strongly comparable) documents NE coverage and the document structural complexity is the same (or at least very close) for both languages, thus the system performance on the data, even if from two different languages, can be compared.

As *TildeNER* relies on the *StanfordNER* CRF classifier, for comparative evaluation a Stanford NER model[5] that

[5] StanfordNER English model from University of Stanford: „*conll.distsim.iob2.crf.ser.gz*", available for download from: http://nlp.stanford.edu/software/crf-faq.shtml (point 11).

achieves an F-measure of 93.0 for English on the "*CoNLL 2003 testa*" data set[6] was selected.

For the comparative evaluation a set of 10 documents (5 parallel and 5 strongly comparable) was selected. The comparable documents are Wikipedia articles and European Commission bilingual news articles, but the parallel documents are legal documents. NEs in both languages were annotated by a human annotator in order to create a reference (gold) data set for evaluation. The corpora statistics is shown in Table 5.

NE Type	**English**	**Latvian**
ORGANIZATION	441	404
LOCATION	291	329
PERSON	113	148
Total	**845**	**881**

Table 5: Comparative evaluation corpora statistics for English-Latvian.

The NE types were limited to organization, person and location. The evaluation results are shown in Table 6.

	Precision	**Recall**	**F-measure**
StanfordNER			
LOCATION	37.5	31.91	34.48
PERSON	37.12	45.37	40.83
ORGANIZATION	60.89	**70.89**	65.51
Latvian bootstrapped for better precision			
LOCATION	**76.47**	39.63	52.21
PERSON	**76.27**	30.41	43.48
ORGANIZATION	**93.16**	44.14	59.90
Latvian bootstrapped for better F-measure			
LOCATION	63.85	**50.61**	**56.46**
PERSON	54.08	**71.62**	**61.63**
ORGANIZATION	77.82	56.86	**65.71**

Table 6: English-Latvian comparative evaluation results.

The comparative evaluation results suggest that even if the results of *TildeNER* are lower than state-of-the-art English NER system results, those cannot be compared without taking test set characteristics into account. The results also suggest that *TildeNER* for Latvian performs slightly better for location and person name NEs on the 10 document comparative evaluation scenario.

One important note when analysing the results has to be also taken into account – the test set of the comparative evaluation is more in favour of the *TildeNER* Latvian NER system as that has been trained on a mixed set of documents including also Wikipedia articles, which are out of domain articles for the *StanfordNER* English model. Nevertheless, the methodology of bilingual comparative evaluation is a means to compare NERs from different languages.

5. Conclusion

In this paper the author presented *TildeNER* - a NER system developed for two Baltic languages for which supervised and semi supervised ML methods for NER had not been applied before. Although, the results show improvements in F-measure using raw data refinement methods as well as F-measure targeted bootstrapping, the methods have to be improved in order to make a significant increase over the supervised learning models.

Refinement methods and their capability in finding new and unseen data is one of the most important requirements for a successful NER model bootstrapping system that is based on supervised learning-based classification.

The toolkit *TildeNER* offers large configuration possibilities for various NER tasks (aid in question answering, automatic gazetteer extraction, machine translation, keyword extraction, etc.) where different requirements for higher precision or higher F-measure can be set.

TildeNER is released under the Apache 2.0[7] licence and can be freely acquired through the *Toolkit for multi-level alignment and information extraction from comparable corpora,* a public deliverable of the ACCURAT project (http://www.accurat-project.eu/index.php?p=toolkit).

Future work on *TildeNER* will involve more fine-grained Latvian and Lithuanian morpho-syntactic feature integration in the CRF classifier. Currently the whole morpho-syntactic tag is used as a single feature function, ignoring that some of the properties within the positional tag may be independent and can be used, for instance, in NE border disambiguation, category classification, etc. Also much can be done with refinement methods in order to find better candidates in bootstrapping as well as to improve tagging quality in terms of precision and recall.

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[6] As reported by University of Stanford in: http://nlp.stanford.edu/software/crf-faq.shtml (point 11)

[7] Apache 2.0 licence: http://www.apache.org/licenses/LICENSE-2.0.html

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